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An Analytical Model for the Treatment and Evacuation of Casualties in a Low-Intensity Conflict

by

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Submitted in partial fulfillment
of the requirements for the degree of

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ABSTRACT

This thesis studies the treatment and evacuation of casualties in a Low-Intensity Conflict. The study addresses the effects of the evacuation policy at the medical battalion level, or echelon. The evacuation policy assigns a threshold number of days to guide surgeons in deciding which casualties should be treated and which should be evacuated. The main tradeoff in choosing this policy involves either treating and returning casualties to duty, or evacuating casualties to maintain a reserve capacity for unexpected casualty arrivals. The study develops simple analytical models which provide basic quantitative measures of the effects of the evacuation policy, and it establishes a framework around which more complex models may be built. The potential of the model is illustrated by examining a specific scenario. This analysis provides the decision maker with estimates of the number of available beds, the proportion of patients returned to duty, and the probability of being able to accommodate a mass arrival of casualties.

THESIS DISCLAIMER

The reader is cautioned that computer programs developed in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logic errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

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I. INTRODUCTION

This thesis studies the process of casualty treatment and evacuation by a Naval medical battalion in a Low-Intensity Conflict (LIC). The analysis focuses on the optimal policy for evacuating casualties. This chapter presents the background for understanding the military and medical scenarios. Following chapters fully define the problem, develop appropriate models, and present the results of the model as applied to a specific decision-making scenario.

A. PROBLEM SETTING

In the late 1980's and early 1990's the Marine Expeditionary Force (MEF) has been deployed as the initial force in United Nation (UN) peace-keeping and relief efforts. The MEF, consisting of a Marine division and its support services, may deploy to foreign and hostile environments for possibly two to three months. Support services for the MEF include a Naval medical battalion to provide medical support for approximately 15,000 marines.

1. Military Scenario

The type of combat environment expected for this type of operation can be termed a *Low-Intensity Conflict* (LIC). In the UN peacekeeping role, the MEF may deploy to an area where the greatest medical threat is that of local disease.

Marines might also expect a low rate of combat injuries. Beyond these expected disease and battle casualties, there is typically the potential for an unexpected episode resulting in many casualties.

2. Medical Conditions

All casualties can be placed into two distinct classifications: *Wounded in Action* (WIA), and *Disease and NonBattle Injuries* (DNBI). For medical purposes, the arrival and treatment rates for these casualty classes are considered separately. In the LIC environment, arrival rates of DNBI and WIA casualties should normally be low. However, a large casualty occurrence could result in sudden, but short-lived, increase in the WIA rate.

In this scenario, the medical planners' decisions include the determination of an evacuation policy. The *evacuation policy* stipulates the maximum amount of time that a patient may remain at a treatment facility before he should be evacuated. This policy implicitly assumes that if patients are allowed to remain in beds for a longer period of time, then more of these patients will be returned to duty. However, the resulting larger population of recovering patients reduces the facility's ability to accommodate a sudden influx of wounded casualties.

Under the conditions of this scenario, medical planners should set an evacuation policy that allows for the

accommodation of an unexpected and large casualty "spike." Simultaneously, planners should implement a policy that results in the return to duty of most patients during day-to-day operations. This fundamental tradeoff forms the basis of the evacuation policy problem.

B. THE EVACUATION POLICY PROBLEM

The goal of this thesis is to model the casualty treatment and evacuation process, and to study quantitative methods to aid decision makers in setting the evacuation policy.

> *The evacuation policy sets a threshold number of days for patient treatment. If the evaluation of an incoming casualty indicates a treatment time less than this threshold, then the casualty is treated in anticipation of return to duty. Otherwise, the casualty is stabilized and evacuated. Henceforth, this treatment threshold is synonymous with the evacuation policy.*

Analysis is limited to a LIC scenario with normally low casualty rates that are within the capacity of the medical battalion's resources. Based on this constraint, we can analyze the impact of the evacuation policy on the medical battalion's effectiveness.

This thesis begins by discussing the problem's parameters and tradeoffs, and identifying appropriate assumptions and measures of effectiveness. The study continues by developing

the framework for a real time decision aid based on analytical techniques. The resulting model is used to analyze a decision problem supplied by the Naval Health Research Center (NHRC) to illustrate the potential usefulness of these analytical techniques. Finally, the study addresses some modeling shortcomings and possible alternate models.

II. PROBLEM DISCUSSION

A. ASSUMPTIONS AND PARAMETERS

In approaching this problem, the first step is to define the *system* of interest, namely the medical battalion. Figure 1 is a flow diagram of the general casualty treatment and evacuation process. The medical battalion's position in the medical evacuation chain is evident in this figure.

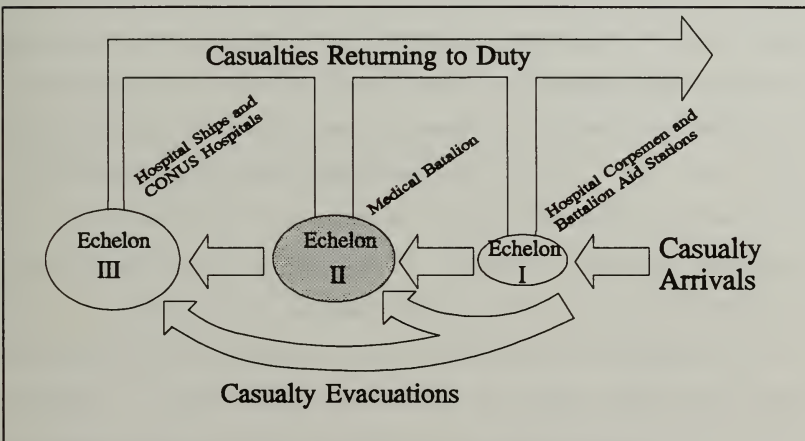

Figure 1 General Casualty Treatment Flow Diagram.

To concentrate analysis on the medical battalion, several assumptions are made to reduce Figure 1 to an uncomplicated representation of the medical battalion. The resulting structure consists of the medical battalion, its input of

casualties, and its output of patient evacuations and returns to duty.

From this point on, the term *casualties* is used to describe those wounded or injured personnel that have not yet received treatment by the medical battalion. *Patients*, on the other hand, are those personnel that have been admitted to the medical battalion for treatment.

1. Casualty Arrivals

As indicated in Figure 1, the medical battalion receives casualties directly from the field or by way of battalion aid stations. Experience has shown that emergency treatment by company medics or battalion aid stations greatly increases a casualty's chance of surviving and returning to duty [Ref. 1]. This study assumes that this preliminary treatment is reflected in the model for the distribution of casualty treatment times. This assumption allows us to disregard the point of origin of arriving casualties.

Besides the point of origin, consideration should be given to the types of arriving casualties. Ideally, casualties can be categorized in terms of specific types of wounds, diseases and injuries. For some specific scenarios, in which a limited number of ailments are expected, this approach might be feasible. However, this study considers only the military's two general casualty types: Disease and Nonbattle Injury (DNBI), and Wounded in Action (WIA). These

categories are well understood by military and medical planners, and current procedures are in place to estimate casualty rates for each category.

2. Patient Departures

This analysis assumes that patients leave the medical battalion for one of two reasons: return to duty, or evacuation. The focus is maintained on the tradeoff between casualty evacuation and return to duty by not analyzing for mortality effects. If desired, the small number of patient deaths could be addressed, possibly by including these figures with patient evacuations. However, mortality rates in the medical battalion should be low enough in this type of conflict so that the results are not affected.

3. Medical Unit Operations

A significant assumption for this study pertains to the clinical aspects of casualty treatment. At many points in the treatment of casualties, doctors make clinical evaluations, or forecasts, that affect the treatment process. Examples of this include the triage of incoming casualties and the day-to-day evaluation of patient conditions.

Triage is "... the sorting and assignment of treatment priorities to various categories of wounded." [Ref. 2] The triage decisions determine whether or not a casualty is admitted for treatment, stabilized for evacuation, or immediately returned to duty. Thus, the triage officer is

forecasting the required treatment time and effort required for each casualty. For this study, triage and all other clinical forecasts are assumed to be made perfectly.

From a logistics standpoint, this analysis does not account for limited transportation or supply resources for the medical battalion. The model assumes that assets are always available to transport casualties, and supply support is always sufficient to support full bed utilization. The model leaves it to the medical commander to decide the required amount of transportation and supply support based on the calculated measures of effectiveness.

B. POLICY TRADEOFFS

This study assumes that the user of the model is an expert decision maker. In other words, the decision maker understands the tradeoffs that must be made in providing the best medical service for a Marine division. A discussion of these tradeoffs underscores the importance of the evacuation policy.

1. Mission

An understanding of the medical battalion's mission is required to grasp the significance of these tradeoffs. This mission, according to *Emergency War Surgery*, follows:

> The ultimate goal of combat medicine is the return of the greatest possible number of soldiers to combat and the preservation of life and limb in those who cannot be returned. [Ref 2]

Clearly the evacuation policy greatly affects this mission. This policy directly influences the medical battalion's ability to fulfill both aspects of its mission.

2. Primary Effects

By setting the evacuation policy at a large value, many patients can eventually be returned to duty. This policy causes more of the medical battalion's beds to be occupied. However, this increased bed utilization diminishes the ability of the medical battalion to respond to a large surge in casualty arrivals.

A large group of casualties arriving to find a full medical facility results in casualties either waiting for treatment, or being evacuated unnecessarily. This situation is undesirable for the following reasons:

> ... those casualties most likely to return to duty will be sent farthest away, since they are the most transportable and in the best condition to tolerate evacuation. Those casualties least likely to return to duty will be kept in forward areas, due to their serious and unstable condition. These may then pose a much greater logistical demand upon the system due to the serious nature of their wounds requiring intensive care. [Ref. 3]

If planners choose a shorter evacuation policy, the resulting bed utilization is much lower. This has the advantage of allowing the accommodation of a large group of casualties. However, this policy results in fewer patients returning to duty.

Thus, the medical battalion's patient returns to duty, and its ability to accommodate large casualty arrivals, are directly affected by the choice of evacuation policy.

3. Secondary Effects

Besides these considerations, other tradeoffs accompanying the evacuation policy lead to secondary effects. These effects are termed secondary because of their dependence on the previously discussed factors. They are not necessarily secondary in importance to the military commander. Relevant factors are typically hard to measure, thus making quantitative analysis of their effects difficult. Some of these factors include:

- Higher bed utilization requires increased medical supply support.
- Increased evacuation rates result in greater transportation requirements.
- Increased evacuation rates also generate an inflow of inexperienced replacements to the combat units.
- Any inability of the medical battalion to handle mass casualties results in unnecessary casualty evacuations and treatment delays.
- This inability also reduces the confidence and morale of the combat units. [Ref. 1]

These are only a few of the many effects that a medical planner may consider in choosing an evacuation policy. The importance of each of these factors varies depending on the actual military situation. Consequently, we define a few

important measures that may help the planner estimate the actual effects of an evacuation policy.

C. MEASURES OF EFFECTIVENESS

Many concepts used in queueing theory are applicable to the evacuation policy. This discussion presents some of these concepts as they pertain to the evacuation policy problem.

1. Primary Measures

The medical battalion's mission effectiveness is primarily measured by the flow of patients returning to duty and the ability to treat the majority of arriving casualties. In evaluating the medical battalion's ability to treat a large influx of casualties, it is assumed that these mass casualties arrive as a group[1]. Thus, the maintenance of a reserve bed capacity becomes important to the planners.

a. Patient Returns to Duty

The first measure of patient returns to duty is the average, or mean, rate of return to duty, λ_{RTD}. This measure provides a steady-state approximation to the average number of patients returned to duty each day. This measure can assist the medical planner in estimating requirements such as transportation assets.

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[1] This assumption is based on a large casualty influx that lasts for a short time (i.e., $\leq$ 24 Hours) as compared to the campaign time (i.e., $\approx$ 60 to 90 days).

Alternatively, the decision maker may be more concerned with the expected proportion of patients returning to duty, p_{RTD}. This measure provides a more direct indication of the effectiveness of the medical battalion in returning patients to duty.

b. Reserve Capacity

The most straightforward estimate of the medical battalion's reserve capacity is the expected, or average, number of available beds. This provides the medical planner with a measure of long-term effects such as required supply support levels.

Another useful measure is the probability of having at least a specified number of beds available. This provides the planner with an actual probability of accommodating a large casualty surge.

2. Secondary Measures

Beyond these primary measures, some secondary measures of effectiveness further illustrate the effects of the evacuation policy. Some of these measures include:

- The expected rate and number of patient evacuations,
- The expected rate and number of replacements required, and
- The expected number of beds occupied.

By using analytical models, many of these primary and secondary measures of effectiveness can be calculated using a

hand-held programmable calculator. Alternatively, the results can be plotted, for a range of evacuation policies, to provide a graphical representation of the measures of effectiveness. In either case, this analysis results in accessible quantitative measures to assist the medical decision maker with the assignment of an evacuation policy.

III. MODEL STRUCTURE

We now develop an analytical model for the treatment and evacuation process. An analytical model, which captures the essential components of the real problem, offers the advantage of precise, easily calculated measures given some reasonable modeling assumptions.

Figure 2 is a block diagram of the treatment and evacuation model. Development begins with a discussion of the flow parameters for the model, and then addresses the patient treatment time considerations.

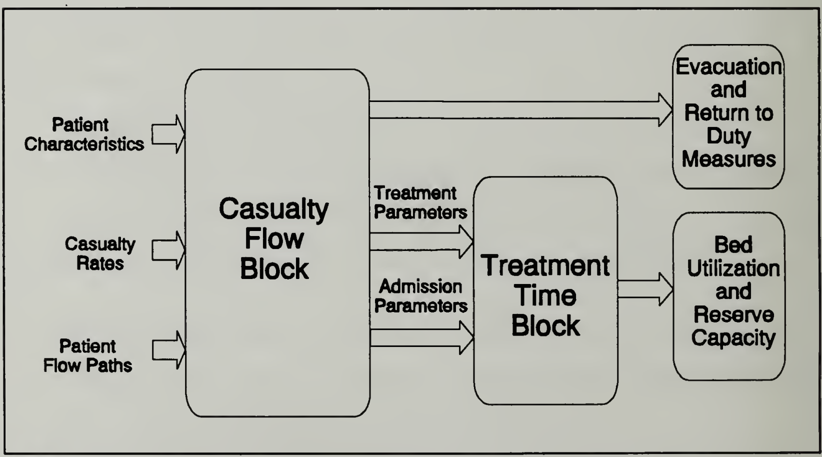

Figure 2 Model Block Diagram.

It is useful to define several terms and indices that are used consistently in the following model development. Some of these include:

Casualty Types (Referenced with the subscript i):

- W = WIA = Wounded in action, and
- D = DNBI = Disease and nonbattle injuries.

Treatment Types (Referenced with the superscript j):

- A = Admissions treated for return to duty, and
- E = Evacuees stabilized before evacuation.

Other (Superscript):

- R = Casualties immediately returned to duty.

A. CASUALTY FLOWS

The flow parameters for the casualty treatment model include patient characteristics, casualty rates, and patient flow paths. These factors affect the medical treatment system and consequently influences our measures of effectiveness.

1. Patient Characteristics

The most important patient characteristics concern the type and severity of arriving casualties' wounds or injuries. Accurate identification and triage of the various casualty severities are crucial to medical operations.

During the triage of incoming casualties, medical commanders can readily figure out the proportion of casualties who are either immediately scheduled for evacuation,

immediately returned to duty, or admitted to the hospital for treatment in anticipation of return to duty. As mentioned earlier, these forecasts by the triage officer are assumed to be made perfectly.

By placing arriving casualties in one of these three groups, we can define the following proportions for i = W and D (DNBI and WIA casualty types)

p_i^E ≡ proportion of arriving type i casualties scheduled for evacuation,

p_i^R ≡ proportion of arriving type i casualties immediately returned to duty, and

p_i^A ≡ proportion of arriving type i casualties admitted to the medical battalion for treatment;

where $p_i^E + p_i^R + p_i^A = 1$.

2. Casualty Rates

Arrival rates for DNBI and WIA casualties are also essential inputs to the model. Casualty rate estimates are normally calculated during the planning process of a military operation. These casualty estimates should be used by commanders to make initial evacuation decisions. However, once the operation begins, actual casualty rate data should be used as a basis for updating the evacuation policy.

Casualty rates are normally expressed as the number of casualties arriving per one thousand combat troops per day. For this analysis, we convert these casualty rates into the following daily rates:

$\lambda_D \equiv$ the average number of DNBI casualties arriving per day, and

$\lambda_W \equiv$ the average number of WIA casualties arriving per day.

Note that these are estimated rates of casualties arriving at the medical battalion for triage. These are not necessarily the rates of patient admission. Patients admitted to the medical battalion include those being treated for return to duty, and those being treated before evacuation.

3. Patient Flow Paths

At this point, it is worthwhile to identify further the different flow paths in the patient treatment model. Figure 3 illustrates these paths as they are determined during the triage process. Notice that some casualties are returned to duty immediately during this screening, and the remaining casualties are admitted to the hospital.

As Figure 3 shows, there are four patient streams being admitted for hospitalization. The DNBI and WIA casualties are shown as distinct flows paths in the triage process. Each of these paths is further split into those patients being treated for return to duty and those being treated before evacuation.

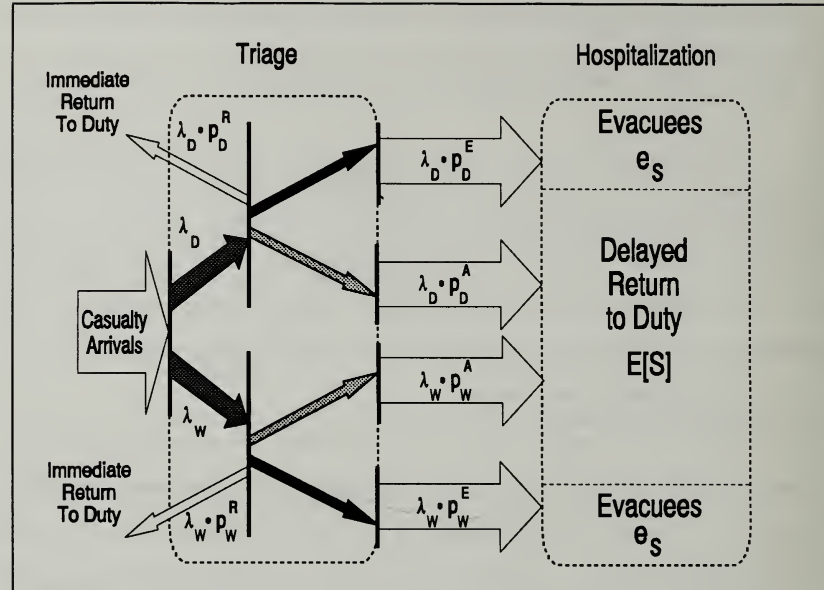

Figure 3 Flow Diagram for Triage and Hospitalization.

Casualties are assumed to arrive according to a Poisson process. Thus, by decomposition, the casualty admission rates for each of these paths can be found by multiplying the casualty arrival rates by the patient proportions:

$$\lambda_i^j = p_i^j \cdot \lambda_i, \ \forall(i,j), \tag{1}$$

where λ_i^j is the admission rate of casualty type i for treatment type j.

B. PATIENT TREATMENT TIMES

We now consider the patient treatment times for each of the patient flow paths. This discussion addresses the decisions affecting the evacuation of arriving casualties, then proposes a model for the patient treatment times.

1. Evacuation Decisions

There are two decisions affecting the evacuation of casualties. These are the evacuation policy and the evacuation schedule. The *evacuation policy*, e_p, was previously defined as the maximum amount of time that a casualty may be treated before he should be evacuated. For those patients identified as evacuees, the *evacuation schedule*, e_s, is an estimate of the amount of hospitalization time needed before their evacuation.

The evacuation schedule accounts for the time needed for some patients to stabilize following emergency surgery. The actual treatment time, for these evacuees, is a random variable. However, previous analysis has shown that the evacuation schedule can be approximated by a fixed value [Ref. 4]. Separate evacuation schedules may be set for DNBI and WIA patients; however, this analysis assumes a single, fixed evacuation schedule for all evacuating casualties. This value represents expected delay time before evacuation for these casualties. Historical estimates provide the evacuation schedule for this analysis.

The evacuation policy is the focus of this study. It is assumed to apply equally for DNBI and WIA casualties. The qualitative effects of the evacuation policy have been briefly discussed. Succeeding analysis concentrates on the quantitative effects of this policy on the medical battalion's effectiveness.

2. Treatment Time Model

For the purposes of this study, *treatment time* is the number of days of treatment needed before allowing a patient to return to duty. For the treatment time model, we consider only those casualties admitted to the medical battalion in anticipation of return to duty. This allows us to more accurately depict the bed utilization of the medical battalion. A representative data set, composed of treatment days required to return patients to duty, forms the basis for the distribution model. These data, provided by the Naval Health Research Center, represent typical casualty treatment times for a LIC scenario. Table I presents these data for both DNBI and WIA casualties.

Table I data indicates the number of instances of treatment days required for return to duty of casualties. This frequency distribution can be modeled with a parametric distribution to provide general analytical results for this study. One must exercise caution when using current data, as it was most likely collected when an evacuation policy was

TABLE I RAW CASUALTY TREATMENT TIME DATA [Ref. 4]

Days	Number of DNBI Cas.	Number of WIA Cas.	Days	Number of DNBI Cas.	Number of WIA Cas.
0	97	650	40	7	0
1	63	10	31	8	2
2	102	14	42	8	1
3	115	25	33	8	1
4	173	10	34	8	1
5	172	31	35	7	2
6	153	24	36	8	1
7	132	18	37	2	2
8	123	18	38	3	0
9	101	25	39	3	1
10	89	13	40	1	0
11	61	10	41	1	1
12	64	10	42	2	0
13	53	8	43	1	0
14	57	11	44	3	0
15	43	8	45	1	0
16	37	14	46	1	0
17	22	10	37	1	0
18	27	10	48	0	0
19	25	14	39	1	0
20	22	10	50	1	1
21	16	7	51	0	0
22	20	8	52	1	0
23	20	8	53	0	1
24	20	2	54	0	1
25	11	3	55	0	0
26	11	8	56	0	0
27	7	8	57	1	0
28	8	2	58	0	0
29	4	2	≥ 59	6	608
			Totals	1930	1616

being used. Thus, the upper tail of the distribution tends to be censored. Despite this property, the data provide a starting point for comprehending the form of the distribution of casualty treatment times.

a. Data Discussion .

The treatment data set not only provides an indication of the distribution of treatment times, but it also provides an estimate of the patient characteristics. The data includes instances of patients who, requiring zero days of treatment, may be immediately returned to duty. In addition, it includes patients requiring more days of treatment than the maximum permitted evacuation policy of 60 days. Analysis of these outliers allows us to estimate the proportion of patients immediately returned to duty.

Those patients requiring zero days of treatment typically suffer from minor injuries or battle fatigue and do not require hospitalization. Although these arrivals cause short-term stress on the system, they do not affect bed utilization. These casualties may be treated, rest in holding wards for a few hours, and then are returned to duty.

The data in Table I suggests that the following proportions of arriving casualties not requiring hospitalization before return to duty:

$$p_D^R = \frac{97}{1930} = 0.050,$$
$$p_W^R = \frac{650}{1616} = 0.402. \tag{2}$$

These figures may be compared to those recommended by Marine Corps planners of 20% for DNBI and 50% for WIA casualties [Ref. 6]. In reality they are heavily dependent on the tempo and nature of operations, and may vary over a wide range. Fortunately, medical battalion personnel can easily monitor these figures and apply the measured values to actual situations. These data elements, representing minimally-injured casualties not admitted to the hospital, provide an estimate of the proportion of patients that will be returned to duty immediately.

The opposite end of our treatment data spectrum represents casualties with severe injuries and with little hope of return to duty. This group is likely to be a mixture of casualties with stable, but debilitating, injuries and severe life threatening injuries. In either case, the medical battalion should not treat these casualties intent upon their return to duty. Since the maximum allowed evacuation policy is 60 days, only those casualties with treatment times less than 60 days are considered to have any potential for return to duty. These casualties are subject to the evacuation schedule; and, will burden the system until their condition permits evacuation.

These parameters can be expressed in terms of the previously defined casualty proportions, or equivalently in terms of the cumulative distribution function for treatment times. Figure 4 illustrates this point with a plot of the cumulative treatment times for the DNBI data of Table I using a typical evacuation policy of 20 days as an example.

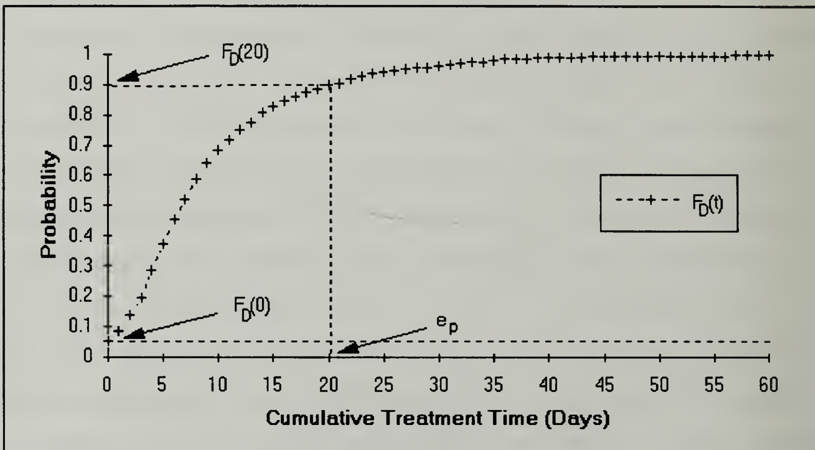

Figure 4 DNBI Cumulative Treatment Time Data.

In this figure, $F_D(t)$ is the cumulative distribution function of treatment time for DNBI casualties. The plot clearly shows the following relationship between the triage proportions and $F_D(t)$ given an evacuation policy of 20 days:

$$p_D^E = 1 - F_D(20),$$
$$p_D^A = F_D(20) - F_D(0), \text{ and} \tag{3}$$
$$p_D^R = F_D(0).$$

The relationships illustrated in Figure 4 and tabulated in Equation (3) also hold for the WIA casualty type.

b. Distribution Fitting

The remaining data in Table I represents the treatment times of casualties that may be admitted to the medical battalion with reasonable expectation of their return to duty. These data are used to estimate an approximate distribution of treatment times for all return-to-duty patients. WIA and DNBI data from Table I were analyzed separately using the distribution fitting tools in AGSS[2]. In both cases, a *lognormal distribution* provides a better fit than alternatives such as the exponential and Weibull. Figure 5 shows the DNBI data from Table I for treatment days ranging from 1 to 59. This figure illustrates the lognormal's more accurate approximation of the distribution of treatment time data as compared to the other two distributions.

For the DNBI data, the resulting lognormal distribution had a chi-square goodness of fit significance

[2] A Graphical Statistical System (AGSS) is IBM's commercial equivalent to the beta test package, GRAFSTAT, used at the Naval Postgraduate School.

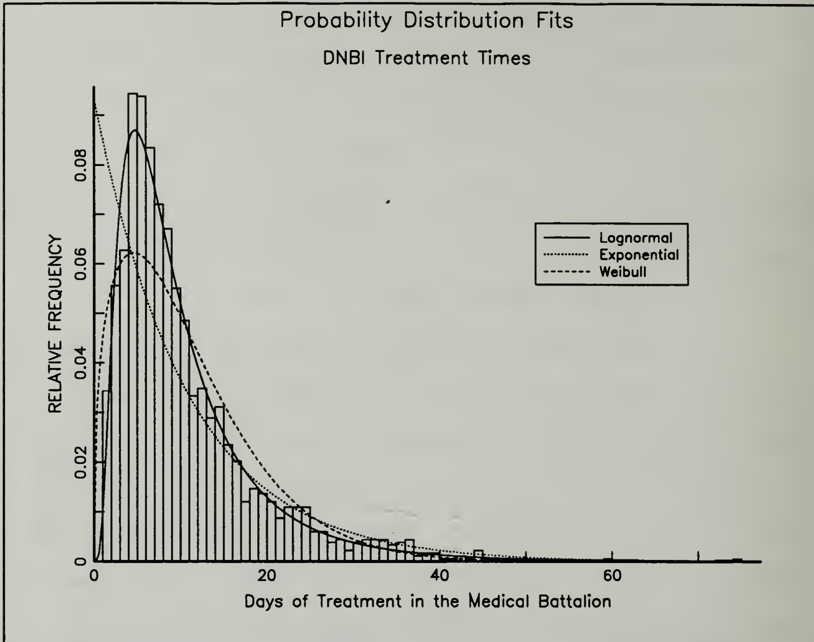

Figure 5 DNBI Data Histogram and Distribution Fits.

level of 0.042. The fit of the WIA data resulted in a significance level of 0.0054. Appendix A contains the details of this data analysis. The resulting lognormal distributions are accepted as reasonable approximations of the WIA and DNBI data in the range from 1 to 59 treatment days.

C. MODEL SUMMARY

At this point, the treatment and evacuation process has been dissected into its basic patient flow and treatment components. Figure 3 provides a good summary of these

components. The figure clearly shows the four patient flow paths as they are admitted to the medical battalion for treatment. The proportion of patients along each path is determined by the distribution of the casualty severities and the evacuation policy.

The distribution of treatment times, resulting from the analysis of Table I data, is the mixed distribution, defined by:

$$F_i(t) = F_i(0) + \overline{F_i}(0)\int_0^t g_i(t)\,dt, \forall i, \tag{4}$$

where $g_i(t)$ is the lognormal probability distribution fitted in the previous section.

These modeling elements may now be blended to determine several measures of effectiveness for the medical battalion. The resulting measures aid the decision maker in selecting the appropriate evacuation policy for the medical battalion.

IV. MODEL OUTPUTS

A. BED UTILIZATION

Several measures of bed utilization are developed in this section by combining the treatment time model with the input flow parameters. The average, or mean, number of available beds is the initial measure of bed availability. Often, an estimated probability of accommodating a group of casualty arrivals may be more useful than a simple expected-value estimate for available beds. For this measure, we must approximate the probability distribution of bed occupancy. An Erlang-B loss model is developed for this purpose. Finally, the characteristics of the Low-Intensity Conflict allow the use of a simpler Gaussian model to approximate the distribution of bed occupancy.

1. Expected Value Approach

Assuming a maximum bed capacity, k, for the medical battalion, the expected number of available, or empty, beds is the maximum bed capacity minus the expected number of beds occupied, or

$$E[N_{av}] = k - E[N_{oc}] \tag{5}$$

where $E[N_{oc}]$ is the expected number of occupied beds, and $E[N_{av}]$ is the expected number of available beds. Thus, we need to estimate the number of occupied beds, $E[N_{oc}]$.

As the flows paths in Figure 3 show, bed occupancy is made up of patients from four separate flow paths. Considering the contribution to bed utilization from each of the four paths, $E[N_{oc}]$ can be found by

$$E[N_{oc}] = \sum_{\forall(i,j)} E[N_i^j] = E[N_D^A]+E[N_W^A]+E[N_D^E]+E[N_W^E]\,, \qquad (6)$$

where $E[N_i^j]$ is the expected number of beds occupied by type i casualties undergoing type j treatment.

Each term in Equation (6) can be found by applying Little's result. This result

> ... states that the average number of customers in a queueing system is equal to the average arrival rate of customers to that system, times the average time spent in that system. [Ref. 7]

For the medical battalion, this implies that the average number of occupied beds is equal to the average admission rate of patients, multiplied by the average treatment time for those patients.

In applying Little's result, this analysis assumes that the medical battalion is never full and casualties do not queue. Thus, average time in the system is the same as the average treatment time. With this assumption, applying

Little's result to each term in Equation (6) yields the following equation:

$$E[N_{oc}] = \sum_{\forall(i,j)} (\lambda_i^j \cdot E[S_i^j]), \tag{7}$$

where λ_i^j is the average arrival rate, and $E[S_i^j]$ is the average treatment time, for each casualty type i and treatment type j.

The terms in Equation (7) can be found based on the parameters already introduced. Given the casualty proportions, estimates of the arrival rates may be calculated from the casualty arrival rates as suggested by Equation (1). Furthermore, the expected treatment time for evacuating patients depends only on the evacuation schedule, which is assumed constant for this analysis:

$$E[S_D^E] = E[S_W^E] = e_s. \tag{8}$$

This leaves $E[S_D^A]$ and $E[S_W^A]$ as the only still unknown terms in Equation (7).

Recalling the casualty treatment time distributions, from Equation (4), defined in terms of $g_i(t)$, we can find the expected treatment time for patients being treated in anticipation of returned to duty by:

$$E[S_i^A] = \overline{F_i}(0) \int_{0^+}^{e_p} t \cdot \frac{g_i(t)}{G_i(e_p)} dt, \ \forall i. \tag{9}$$

Considering this relationship, the terms in Equation (7), for return-to-duty patients, can be written as:

$$\lambda_i^A \cdot E[S_i^A] = \lambda_i \cdot p_i^A \cdot \overline{F_i}(0) \int_{0^+}^{e_p} t \cdot \frac{g_i(t)}{G_i(e_p)} dt, \ \forall i. \tag{10}$$

But, by recognizing that

$$G_i(e_p) = p_i^A = F_i(e_p) - F_i(0), \ \forall i, \tag{11}$$

Equation (10) can be reduced to:

$$\lambda_i^A \cdot E[S_i^A] = \lambda_i \cdot \overline{F_i}(0) \int_{0^+}^{e_p} t \cdot g_i(t)\, dt, \ \forall i. \tag{12}$$

We now have all the terms needed to calculate the expected number of available beds in the medical battalion. The expected number of *occupied* beds becomes[3]:

$$\begin{aligned} E[N_{oc}] = {} & \lambda_D \cdot \overline{F_D}(0) \int_{0^+}^{e_p} t \cdot g_D(t)\, dt \\ & + \lambda_W \cdot \overline{F_W}(0) \int_{0^+}^{e_p} t \cdot g_W(t)\, dt \\ & + (\lambda_D^E + \lambda_W^E)\, e_s \end{aligned} \tag{13}$$

where the flow rates λ_D and λ_W are given, and the evacuation decisions e_p and e_s are constants. The expected number of

---

[3] This result assumes that DNBI and WIA casualties are sorted based on the same evacuation policy. If desired, separate evacuation policies could certainly be used.

available beds is found by subtracting the result from Equation (13) from the total bed capacity of the medical battalion (See Equation (5)).

This measure of the expected number of available beds may not be sufficient for the medical decision maker. Often, he may wish to know the probability of at least a specific number of beds being available. This type of measure requires a more detailed treatment model.

2. Erlang-B Loss Model

The characteristics of the medical facility lead to the Erlang-B loss model. This model, originally for telephone switching systems, provides an initial off-the-shelf but reasonably appropriate analytical model for the present situation.

The Erlang-B model (Also termed the Erlang loss system) is equivalent to the M/M/k/k service system, in which the M/M/k/k notation describes a service facility receiving Poisson arrivals, with exponential service times, and k servers with no holding or queueing capacity.

In this system, *customers* (i.e., casualties) arrive according to a time-homogeneous Poisson process. If at least one of the k *servers* (i.e., hospital beds) is available then the customer enters the system and spends an exponentially distributed time in service. If all of the k servers are busy (i.e., all beds are full), the system is at capacity. A

customer who arrives when all of the servers (beds) are occupied is lost from the system.

For this model, the steady-state probability of being in any state n, namely P_n, can be found by evaluating the formula:

$$P_n = \frac{(\lambda/\mu)^n/n!}{\sum_{i=0}^{k} (\lambda/\mu)^i/i!}, \quad n = 0,1,2, \ldots, k, \tag{14}$$

where
λ is the rate of the Poisson arrival process;
μ is the rate of customer (casualty) service;
n is state of the system; and
k is the number of servers (beds) in the system.

If we define S as the service time, then the expected or average service time, E[S], is $1/\mu$. By substituting for μ in Equation (14) it follows that

$$P_n = \frac{(\lambda \cdot E[S])^n/n!}{\sum_{i=0}^{k} (\lambda \cdot E[S])^i/i!}, \quad n = 0,1,2, \ldots, k. \tag{15}$$

The following is an important fact: if we now consider the system M/G/k/k, where the service times have any general distribution (denoted by G), it can be shown that Equation (15) continues to hold for this more general system. It is said that the Erlang-B formula is *insensitive* to the form of the service time distribution, being dependent only on the mean service time. The resulting model is the *Erlang loss system*. [Ref. 8]

To apply these results to the medical battalion, we must first define the combined arrival rate, λ_T:

$$\lambda_T = \lambda_D + \lambda_W, \tag{16}$$

and the combined mean service time, $E[S_T]$:

$$E[S_T] = \frac{E[N_{OC}]}{\lambda_T}, \tag{17}$$

where $E[N_{OC}]$ is found by Equation (13). Substituting these results into Equation (15), we find that:

$$p_n = P(N_{oc}=n) = \frac{(\lambda_T \cdot E[S_T])^n/n!}{\sum_{i=0}^{k} (\lambda_T \cdot E[S_T])^i/i!}, \quad n = 0,1,2,\ldots,k. \tag{18}$$

Since $N_{oc} = k - N_{av}$, the probability of at least n beds being empty, $P(N_{av} \geq n)$, is derived by:

$$\begin{aligned} P(N_{av} \geq n) &= P(k - N_{oc} \geq n) \\ &= P(N_{oc} < k-n) = \sum_{i=0}^{k-n-1} p_i. \end{aligned} \tag{19}$$

The insensitivity of this result to the treatment time distribution makes the Erlang-B model a robust model for analyzing the bed occupancy level of the Medical Battalion.

3. Normal Approximation

The nature of this problem allows us to apply a normal approximation to the Erlang-B model results. In the LIC

scenario, we are assuming that the steady-state arrival rates are within the capacity of the medical battalion. This assumption allows the medical battalion bed system to be modeled as an *infinite server queue.*

This assumption implies that the distribution of p_n in Equation (18) is approximately Poisson with parameter $\lambda_T \cdot E[S_T]$, or $E[N_{oc}]$. Further, since the expected number of beds occupied is greater than 20 for the scenario of interest, the distribution for p_n can be approximated as normal.

Thus, given the expected value of the number of occupied beds, $E[N_{oc}]$, the distribution for N_{oc} is approximately normal with mean and variance equal to $E[N_{oc}]$. Using this fact, we can find the $P(N_{av} \geq n)$ in terms of the standard normal random variable z as follows

$$
\begin{aligned}
P(N_{av} \geq n) &= P(k - N_{oc} \geq n) \\
&= P(N_{oc} \leq k-n) \\
&= P\left(\frac{N_{oc} - E[N_{oc}]}{\sqrt{E[N_{oc}]}} \leq \frac{k-n-E[N_{oc}]}{\sqrt{E[N_{oc}]}}\right) \\
&\approx P\left(z \leq \frac{k-n-E[N_{oc}]}{\sqrt{E[N_{oc}]}}\right) \\
&= \Phi\left(\frac{k-n-E[N_{oc}]}{\sqrt{E[N_{oc}]}}\right).
\end{aligned}
\tag{20}
$$

The accuracy of this normal approximation depends on the patient admission rates and their mean service times. Analysis found that the normal approximation is accurate up to

a bed utilization of approximately 0.90, where *bed utilization*, ρ, is

$$\rho = \frac{\lambda_T \cdot E[S_T]}{k} = \frac{E[N_{oc}]}{k}. \tag{21}$$

For the LIC, the bed utilization is typically large enough to allow the use of the normal approximation. At the same time, the bed utilization small enough to justify the use of the Poisson approximation to the Erlang model.

The normal approximation provides a second and, when applicable, convenient method to evaluate the distribution of bed occupancy. Figure 6 shows a comparison between the Erlang-B results and those found with the normal approximation[4]. It is clear from this figure that the normal approximation is almost indistinguishable from the Erlang model using reasonable parameters for casualty rates, treatment times and evacuation policies.

B. RETURN TO DUTY

The other primary measure of effectiveness concerns patient returns to duty. Assuming perfect forecasting during the triage process allows a direct calculation for the patient returns to duty.

---

[4] The Erlang-B distribution was solved analytically using the algorithm found in Appendix B.

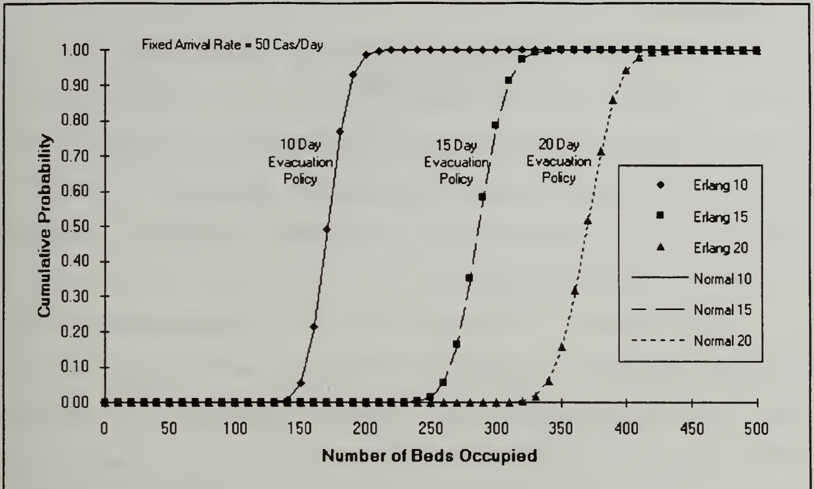

Figure 6 Normal Approximation to the Erlang Model.

For a given evacuation policy, e_p, the proportion of patients returning to duty following treatment is the cumulative distribution of treatment times, for DNBI and WIA casualties, evaluated at e_p. Assuming perfect forecasting, all treated patients eventually return to duty. Thus, the total proportion of arriving casualties returning to duty, p_{RTD}, is:

$$
\begin{aligned}
p_{RTD} &= p_i^A + p_i^R \\
&= 1 - p_i^E, \ \forall i.
\end{aligned}
\tag{22}
$$

In a more complex treatment process model, the uncertainty of the triage process leads to some admitted patients not returning to duty.

C. SUMMARY

The complete casualty treatment model provides the decision maker with two general measures of effectiveness: patient return-to-duty measures and bed utilization measures. Each of these general results may be evaluated by medical planners, within the current mission and situation, to assist in their decision making.

An advantage of this model is its design allowing for a variety of specific measures. For this study, however, the model results are demonstrated based on the previously defined measures of effectiveness.

V. MODEL RESULTS

The models developed in the preceding chapters may now be applied to a specific problem supplied by the Naval Health Research Center. Numerical and graphical results are presented to illustrate the potential for these types of analytical models.

All calculations and plotting for this analysis were performed in Microsoft Excel 4.0. A sampling of the Excel worksheets is contained in Appendix C.

A. NUMERIC INPUTS

The proposed problem considers a medical battalion with a 540-bed capacity. This facility is providing medical support for a combat force of 15,000 troops. The estimated casualty rates for this operation are:

DNBI rate = 3.5 per 1000 strength per day, and

WIA rate = 1.5 per 1000 strength per day.

Beyond these steady-state rates, the enemy is believed to have the capability to inflict a one-time only WIA rate of 15 per 1000 strength for one day.

These casualty rates are converted to this study's notation by:

$\lambda_D = 3.5 \times 15 = 52.5$ Casualties/Day,

$\lambda_W = 1.5 \times 15 = 22.5$ Casualties/Day,

$\lambda_{Max} = 15 \times 15 = 225$ Casualties/Day.

Further, the maximum one-day increase in the number of patient admissions is calculated as

$$\begin{aligned} \text{Casualty Spike} &= (\lambda_{Max} - \lambda_W) \times (1 - p_W^R) \\ &= (225 - 22.5) \times 0.598 \\ &\approx 121 \text{ patients.} \end{aligned}$$

Additional numeric inputs include:

$k = 540$ beds (From the problem statement), and

$e_s = 4$ days (Historical estimates [Ref. 4]).

Parameters for the lognormal models are (See Appendix A):

$\mu_D = 2.1$ and $\sigma_D = 0.737$,

$\mu_W = 2.25$ and $\sigma_W = 0.75$.

These values comprise the numeric inputs to the models developed in the previous chapters. Using these figures, baseline results are calculated for the measures of effectiveness. In addition, some parameters are varied to provide some sensitivity analysis for the results.

B. BED UTILIZATION RESULTS

We begin by estimating the expected number of available beds, $E[N_{av}]$, for a range of evacuation policies. Numerical evaluation of Equations (5) and (13) allows us to estimate

these expected values. Figure 7 plots the expected number of beds available versus the evacuation policy. For this scenario, this figure suggests an evacuation policy of 14 days to accommodate the maximum one-day casualty arrival event, or spike.

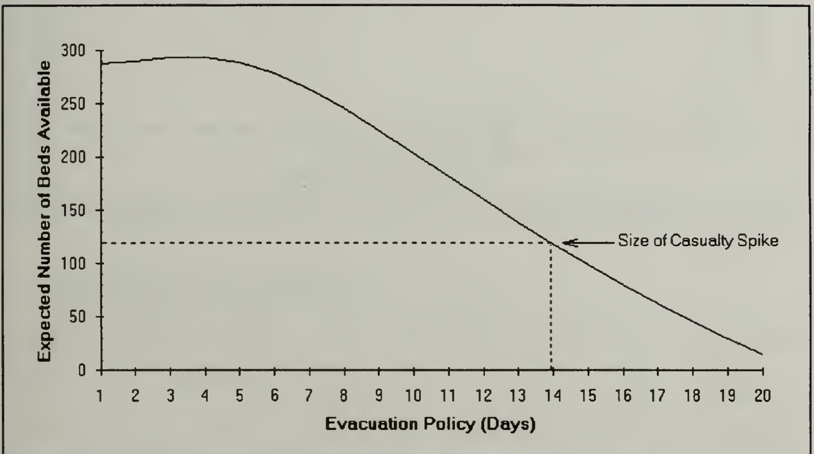

Figure 7 Results for Expected Number of Beds.

We may now estimate the medical battalions' ability to accommodate the large casualty arrivals in terms of a confidence level. The normal approximation model was used to find a 95% confidence level of available beds. These results are shown in Figure 8. Notice in this figure that the indicated evacuation policy has been reduced to between 12 and 13 days. Thus, the recommended evacuation policy would be 12 days.

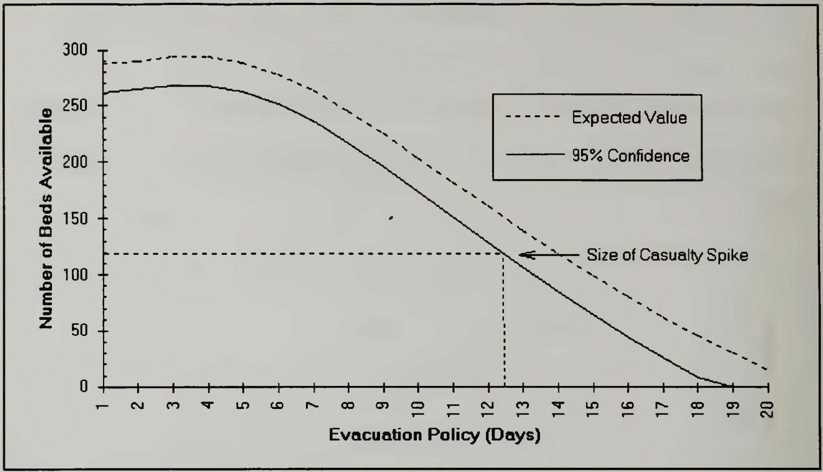

Figure 8 Results for N_{av} with 95% Confidence Level.

Considering these results, Figure 9 was created to examine the range of feasible evacuation policies for our estimated casualty spike. For a casualty spike of 125, which approximates the parameter for our problem, the evacuation policy should be less than 17 days. Between 17 and 10 days, the choice depends on the confidence level desired by the decision maker. For evacuation policies less than 10 days, accommodation of a casualty arrival of size of 125 is assured.

These results provide recommended evacuation policies, for this specific scenario, based on bed utilization and a desired confidence level. The decision maker should also consider the effect that the choice of evacuation policy will have on casualty returns to duty.

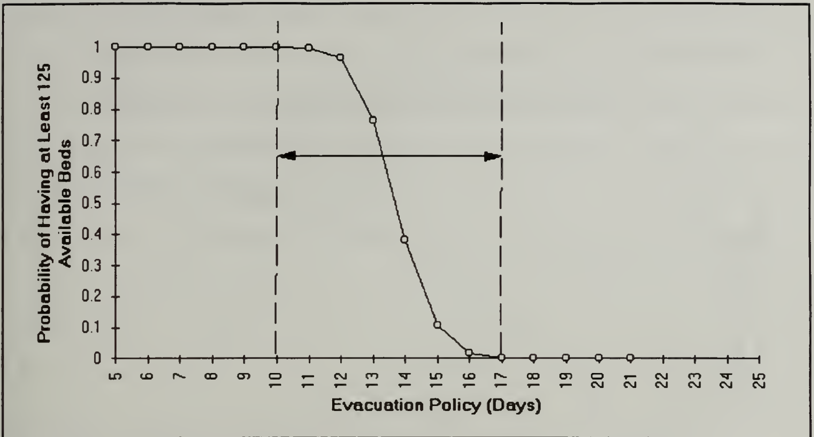

Figure 9 Sensitivity Analysis of Confidence Level.

C. RETURN-TO-DUTY RESULTS

We first consider the proportion of *potential patients* that are returned to duty. This excludes those casualties that do not require hospitalization before return to duty. This exclusion gives a direct indication of the association between returns to duty and bed usage.

Figure 10 illustrates the results for the proportion of patients returned to duty. Recall that this measure is based on the cumulative treatment time distribution, hence its monotonically increasing shape. Evacuation policies, based on the bed utilization results, ranged between 10 and 17 days. These evacuation policies lead to return-to-duty rates of 0.58 and 0.82 respectively. The 12-day evacuation policy, recommended for a 95% confidence of accommodating the casualty

spike, results in a return-to-duty proportion of 0.68, as seen in Figure 10.

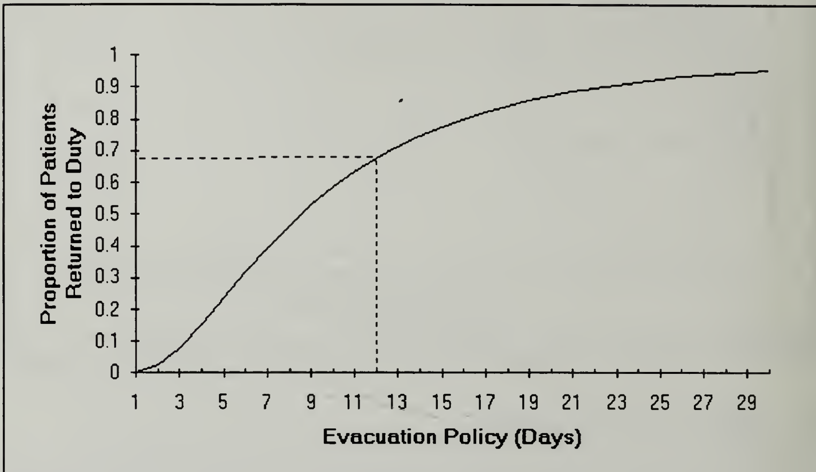

Figure 10 Proportion of Patients Returned to Duty.

D. UTILITY OF RESULTS

For this specific problem, the recommended evacuation policies range from 10 to 17 days. The medical planner must consider the military situation in selecting the threshold number of days for the evacuation policy.

1. Maximizing Return to Duty

To maximize returns to duty, the planner would like to set the evacuation policy at 17 days. This would allow the return of 82% of patients to duty, resulting in very few evacuations (11 casualties per day), thus reduceing the demand on combat transportation resources. An additional benefit is

that, by evacuating fewer casualties out of the combat zone, fewer replacements are required to be sent into the area.

However, to operate under this policy, the medical battalion must be able to sustain an average number of 478 occupied beds. This bed utilization could pose an immense burden on the supply system, besides making the medical battalion highly immobile. Moreover, this evacuation policy allows only a remote chance of accommodating a casualty spike of 120 patients. The consequences of this incapacity to handle incoming casualties are likely to outweigh the advantages of a high rate of return to duty.

2. Assuring the Accommodation of Casualty Spike

On the other hand, if the medical planner wants a 100% probability of accommodating the estimated casualty spike, he would choose an evacuation policy of 10 days. This evacuation policy results in an average of 335 occupied beds. This lower bed utilization results in a more mobile medical battalion requiring much less supply support to sustain its operation.

Unfortunately, this evacuation policy diminishes the proportion of casualties returned to duty to 58%. Along with this reduction comes an increase in casualty evacuations to 26 per day. This is double the number of daily evacuations under the 17-day evacuation policy. Additionally, twice the number of inexperienced reinforcements are called upon to enter the area. Each of these increased flows between the medical

battalion and higher echelons increases the demand on transportation resources.

Clearly the medical planner has to decide which of these, and other, quantitative tradeoffs must be made for his specific scenario. The models developed in previous chapters, and illustrated by the example in this chapter, help the medical planner evaluate the evacuation policy tradeoffs.

VI. CONCLUSIONS

This thesis has developed several analytical models by which the evacuation policy problem can be analyzed quantitatively. The study closes with some comments on the significance of the current model and suggestions for areas of further research.

A. POTENTIAL MODEL USEFULNESS

The analytical models developed in this thesis provide the medical planner with a basis for quantitatively evaluating the effects of various evacuation policies. These models can be used in either the planning or execution of a military operation. For planning purposes, estimated parameters may be input into the model to evaluate medical planning strategies. Operationally, the model can be updated dynamically with current estimates of the input parameters. This allows military commanders to evaluate the current policy and guides them in the selection of a new policy.

The results for this study were calculated using both a hand-held calculator and the PC-based spreadsheet Excel. In military applications, all calculations could be made on a programmable calculator, programmed in any PC-based language, or implemented in most popular spreadsheets.

B. RECOMMENDATIONS FOR FURTHER STUDY

The assumptions made in this study are reasonable for the Low-Intensity Conflict scenario. Complete evaluation of the significance of these assumptions is left to further research. There are also some specific enhancements recommended to the models developed in this study. Model development assumed the same evacuation policy and evacuation schedule for all casualty types. The models could easily be augmented to allow different parameters for each casualty type.

Casualty arrivals are modeled as Poisson for this study. The models could be changed to model group arrivals, thus incorporating extra variability in the Poisson arrival process.

The model for the casualty treatment time distribution developed in this study is based on a single data set. A more robust model might be considered. A possibility is to develop an aggregate model based on a variety of specific disease or injury types. Additionally, the treatment distribution model could be generalized by studying various other casualty data.

Another area for study concerns the modeling of the triage process. This study considered the decisions made by the triage officer to be perfect. Further research might apply decision theory to model imperfect triage, and thus study the uncertainty in the triage decision making.

Finally, some enhancements could be made to account for inaccuracies in estimates of casualty rates, proportions and

treatment times. A general Bayesian model is suggested to allow planners to update these estimated parameters as actual data is obtained during the operation.

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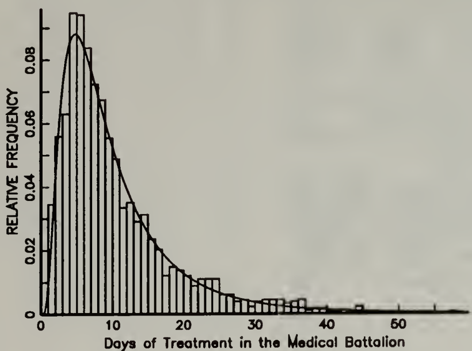
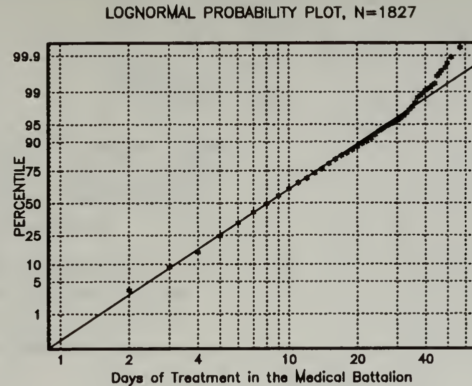
APPENDIX A. AGSS DATA ANALYSIS PLOTS

Lognormal Fit for DNBI Treatment Time



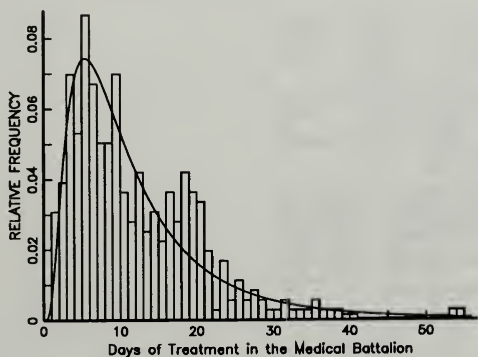


ANALYSIS OF LOGNORMAL DISTRIBUTION FIT

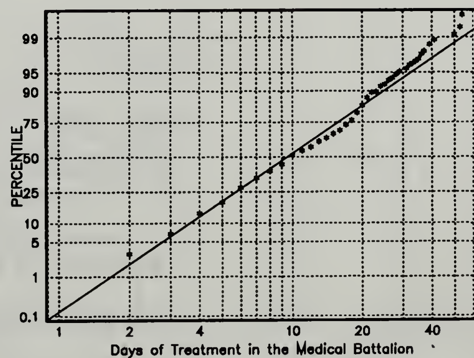
```
DATA          :  DNBIINT[1+ι51;]
SELECTION     :  ALL
X AXIS LABEL:    DAYS OF TREATMENT IN THE MEDICAL BATTALION
SAMPLE SIZE  :   1827
CENSORING     :  GROUPED DATA (CENSORING IS IMPLICIT)
FREQUENCIES  :   DNBIDIST[1+ι51;2]
EST. METHOD  :   MAXIMUM LIKELIHOOD
CONF METHOD  :   ASYMPTOTIC NORMAL APPROXIMATION

                      CONF. INTERVALS      COVARIANCE MATRIX OF
                       (95 PERCENT)        PARAMETER ESTIMATES
PARAMETER  ESTIMATE   LOWER    UPPER        MU           SIGMA
MU         2.0925     2.059    2.128        2.9247E¯4   ¯2.5954E¯6
SIGMA      0.72858    0.70455  0.7526      ¯2.5954E¯6    1.5022E¯4
LOG LIKELIHOOD FUNCTION AT MLE = ¯5844.1

            SAMPLE*     FITTED                GOODNESS OF FIT TESTS
MEAN     :  10.507      10.569             CHI-SQUARE :  56.652
STD DEV  :   8.1485      8.8444             DEG FREED:   40
SKEWNESS:    1.8157      3.0967             SIGNIF     :  0.042274
KURTOSIS:    6.9319     23.864
```

Lognormal Fit for WIA Treatment Time

LOGNORMAL DENSITY FUNCTION, N=358



LOGNORMAL PROBABILITY PLOT, N=358



ANALYSIS OF LOGNORMAL DISTRIBUTION FIT

```
DATA         :  WIAINT[1+ι41;]
SELECTION    :  ALL
X AXIS LABEL:   DAYS OF TREATMENT IN THE MEDICAL BATTALION
SAMPLE SIZE :   358
CENSORING    :  GROUPED DATA (CENSORING IS IMPLICIT)
FREQUENCIES :   WIADIST[1+ι41;2]
EST. METHOD :   MAXIMUM LIKELIHOOD
CONF METHOD :   ASYMPTOTIC NORMAL APPROXIMATION

                      CONF. INTERVALS       COVARIANCE MATRIX OF
                       (95 PERCENT)         PARAMETER ESTIMATES
PARAMETER  ESTIMATE   LOWER    UPPER        MU             SIGMA
MU         2.2501     2.1723   2.3279        0.0015759     ¯0.000012329
SIGMA      0.74914    0.69339  0.8049       ¯0.000012329    0.00080887
LOG LIKELIHOOD FUNCTION AT MLE = ¯1211.5

             SAMPLE*     FITTED                   GOODNESS OF FIT TESTS
MEAN     :   12.26        12.562              CHI-SQUARE :  53.44
STD DEV  :   8.8231       10.899                DEG FREED:  30
SKEWNESS:    1.5218        3.2561               SIGNIF   :  0.0053579
KURTOSIS:    6.3863       26.426
```

APPENDIX B. PASCAL SOURCE CODE

```
Program Evaluate_Erlang;
{ Author : Tracy L. Howard                                    }
{ Date   : March 1993                                         }
{ Use    : Thesis Research                                    }
{    This program evaluates the Erlang-B distribution model }
{ developed in this thesis for comparison with normal        }
{ approximations.                                             }
{    The mean treatment time data is calculated in Excel and}
{ read from an input file.  The output is analyzed in Excel.}

{ The math unit is used for Factorial and Power functions.}
Uses Math;

Const
  MAX_BED_SIZE = 1000;
  MAX_SCENARIO_DAYS = 90;

Type
  DataArray = Array [0..10*MAX_SCENARIO_DAYS] of Real;

  Scenario_Record = Record
                      Evac           : Real;
                      NumBeds        : Word;
                    End;

  Cas_Record = Record
                 Lambda,
                 MST             : Real;
                 FreqAdmitted    : Word;
                 Data            : DataArray;
               End;

  BedArray = Array [0..MAX_BED_SIZE] of Extended;

Var
  Current       : Scenario_Record;

  CumDist,
  BedDistI      : BedArray;

  WIA,
  Combined      : Cas_Record;

  RTD,
  Mu            : Real;
```

```
  Counter,
  I           : Word;

  DataOutFile,
  WIAInFile   : Text;


Procedure InitializeFiles (var WIA_Input, Output: Text);
  {   This procedure assigns the filenames for the input and}
  { output files, then prepares the input file to be read   }
  { and output file to be written. }

  Var I : Word;

  Begin

   { Assigns output file that will be written in comma }
   { delimited format. }
    Assign (Output, 'd:\thesis\dat\output.csv');
    ReWrite (Output);

   { Assigns input file containing the means service times }
    Assign (WIA_Input, 'D:\THESIS\DAT\meansimm.txt');
    Reset (WIAInFile);
    Readln (WIAInFile);

  End; {InitializeFiles}


Procedure  ReadData  (var  Data_File  :  Text;  var  Data  :
DataArray);
  {    This procedure reads the first 300 mean service times}
  { from the input file.  }

  Var Index : Word;

  Begin

   { Initializes the data array to zero.}
    FillChar (Data, SizeOf(Data), 0);

   { Reads the Data in the form of one item per line.}
    For Index := 1 to 300 do
      Readln (Data_File, Data[Index]);

  End; {ReadData}


Procedure Erlang (NumberOfBeds : Word;
                  Lambda, Mu : Real; var Prob : BedArray);
 {   This procedure calculates the probability distribution }
```

```
{ for the Erlang-B model.  Note that this calculation      }
{ involves calculations of the form (X to the nth) divided }
{ by n!.  This algorithm evaluates these terms by brute    }
{ force (i.e., Very large numbers are needed).             }
{   Numerical methods could be used to develop a more      }
{ efficient algorithm.}

 Var I           : Word;
     Rho,
     Numerator,
     Denominator : Extended;
 { Extended type allows Real numbers with }
 { Exponents in the range: -4932 to 4932. }

 Begin

  { Initializes the probability array.}
   FillChar(Prob,SizeOf(Prob),0);

   Rho := Lambda/Mu;

   Denominator := 1.0;

   For I := 1 to NumberOfBeds do Denominator := Denominator
                                  + Power(Rho,I)/Factorial(I);

   For I := 0 to NumberOfBeds do begin

     Numerator := Power(Rho,I)/Factorial(I);
     Prob[I] := Numerator / Denominator;

   End; {For I}

 End; {Erlang}


Begin {Analytical_Model}

 { Bed capacity of the facility}
  Current.NumBeds := 540;

  InitializeFiles (WIAInFile, DataOutFile);

  ReadData (WIAInFile, WIA.Data);

 { Total casualty arrival rate}
  WIA.Lambda:= 100 ;

 {    This loop evaluates the Erlang-B distribution for }
 { evacuation policies from 0 to 30 days in 1/10 of a day}
 { increments.     }
```

```
  For Counter := 1 to 300 do begin

    Current.Evac := Counter/10;

    Mu := 1/Wia.Data[Counter];

    Erlang (Current.NumBeds,WIA.Lambda,Mu,BedDistI);

    FillChar (CumDist,SizeOf(CumDist),0);

    CumDist[0] := BedDistI[0];

   {   This loop writes the cumulative probability  }
   { distribution to the output file.   }
    Write (DataOutFile,(WIA.Lambda/(Mu*Current.NumBeds)),',',
                                                        CumDist[0]);
    For I := 1 to Current.NumBeds do begin

      CumDist[I] := CumDist[I-1] + BedDistI[I];

      Write (DataOutFile,',',CumDist[I]);

    End;
    Writeln(DataOutFile);

  End; {For Current}

  Close (DataOutFile);
  Close (WIAInFile);

End.  {Evaluate_Erlang}
```

APPENDIX C. EXCEL WORKSHEETS

The pages of this appendix contain printouts of selected Excel data worksheets used to calculate the results for this study.

		Evac	Casualty	Arrival	Lognormal Parameters			
	P(Admission)	Sched	Rate	λ	σ	μ	Mean	Std Dev
DNBI	0.94974093	4	3.5	52.5	0.737	2.1	3.74935753	9.100604442
WIA	0.59777228	4	1.5	22.5	0.75	2.25	4.080624335	10.92187251
Total				75				

Max Beds
540

Troops (thousands)
15

Max Daily
121.0488861

t	DNBI G(t)	DNBI g(t)	t*g(t)	E[S]	WIA G(t)	WIA g(t)	t*g(t)	E[S]
1	0.002190226	0.002190226	0.002190226	3.79272329	0.001349967	0.001349967	0.001349967	2.38866819
2	0.028137996	0.025947771	0.051895541	3.74343597	0.018955987	0.017606019	0.035212039	2.367619409
3	0.087115344	0.058977348	0.176932044	3.687422769	0.062369383	0.043413397	0.13024019	2.341668084
4	0.166424061	0.079308717	0.317234868	3.687422769	0.124741249	0.062371865	0.249487462	2.341668084
5	0.252826876	0.086402815	0.432014073	3.769483059	0.196529511	0.071788263	0.358941314	2.384581118
6	0.337887029	0.085060153	0.510360917	3.931053276	0.270603913	0.074074401	0.444446408	2.473140365
7	0.417194039	0.079307011	0.555149076	4.15701662	0.342572273	0.07196836	0.503778521	2.602202436
8	0.488872982	0.071678943	0.573431542	4.429322324	0.410052016	0.067479743	0.539837946	2.763552516
9	0.552476002	0.06360302	0.572427176	4.731354279	0.471950617	0.0618986	0.557087404	2.948558852
10	0.608294958	0.055818957	0.558189565	5.049435566	0.527948392	0.055997775	0.559977753	3.149402358
11	0.656967066	0.048672108	0.535393189	5.37301682	0.578161998	0.050213606	0.55234967	3.359516471
12	0.699255847	0.04228878	0.507465361	5.694323903	0.622938943	0.044776945	0.537323339	3.573647802
13	0.735936485	0.036680639	0.476848302	6.007857839	0.662732573	0.03979363	0.517317184	3.787735559
14	0.767739075	0.03180259	0.445236253	6.309900049	0.698030067	0.035297494	0.494164922	3.998734195
15	0.79532397	0.027584895	0.413773424	6.598083591	0.729312078	0.031282011	0.469230158	4.204428901
16	0.819274452	0.023950482	0.383207718	6.871044633	0.757031385	0.027719307	0.443508907	4.403266898
17	0.840098319	0.020823867	0.354005745	7.128149262	0.781602885	0.0245715	0.417715499	4.594212997
18	0.858233711	0.018135391	0.326437046	7.369284193	0.803400181	0.021797296	0.392351335	4.77663047
19	0.874056604	0.015822893	0.300634976	7.594698936	0.822755892	0.019355711	0.367758502	4.950185078
20	0.88788862	0.013832016	0.276640315	7.804888241	0.839963939	0.017208047	0.34416094	5.114768973
21	0.900004443	0.012115823	0.254432284	8.000505423	0.855282783	0.015318844	0.321695723	5.270441037
22	0.910638555	0.010634112	0.233950457	8.182299144	0.868938995	0.013656212	0.300436673	5.417380531
23	0.919991169	0.009352614	0.215110131	8.351067797	0.881130825	0.01219183	0.280412082	5.555851349
24	0.928233378	0.008242209	0.197813007	8.507627055	0.892031573	0.010900749	0.261617969	5.686174656
25	0.935511559	0.007278182	0.18195454	8.652787182	0.901792691	0.009761117	0.244027935	5.808708089
26	0.941951132	0.006439573	0.167428893	8.787337551	0.910546555	0.008753865	0.227600482	5.923830077
27	0.947659733	0.005708601	0.154132224	8.912036465	0.91840894	0.007862385	0.212284391	6.031928138
28	0.952729903	0.00507017	0.141964769	9.027604824	0.925481178	0.007072238	0.198022672	6.133390249
29	0.957241355	0.004511452	0.130832102	9.134722585	0.931852055	0.006370877	0.184755424	6.228598586
30	0.961262882	0.004021527	0.120645812	9.234027216	0.937599451	0.005747396	0.17242189	6.317925075
31	0.964853972	0.00359109	0.11132378	9.326113547	0.942791771	0.005192319	0.160961902	6.401728339
32	0.968066165	0.003212194	0.102790197	9.411534598	0.947489174	0.004697403	0.150316886	6.480351698
33	0.970944208	0.002878042	0.094975397	9.490803041	0.951744644	0.00425547	0.140430524	6.554121963

E[S] Total	E[N]	Normal Appr	0.95	P RTD
3.371507	252.863		260.9810887	0.002012
3.330691	249.8018		264.2010754	0.026187
3.283696	246.2772		267.9097289	0.081858
3.283696	246.2772		267.9097289	0.157569
3.354012	251.5509		262.3611079	0.240867
3.493679	262.026		251.3484543	0.323593
3.690572	276.7929		235.8414971	0.401341
3.929591	294.7194		217.0428099	0.472128
4.196516	314.7387		196.0801934	0.535369
4.479426	335.9569		173.8943591	0.591226
4.768967	357.6725		151.2196555	0.640226
5.058121	379.3591		128.6038832	0.683043
5.341821	400.6366		106.4401865	0.720385
5.61655	421.2413		84.99949674	0.75293
5.879987	440.999		64.45908584	0.7813
6.130711	459.8033		44.92602653	0.806052
6.367968	477.5976		26.45574205	0.827672
6.591488	494.3616		9.066331376	0.846585
6.801345	510.1009		0	0.863158
6.997852	524.8389		0	0.877707
7.181486	538.6115		0	0.890504
7.352824	551.4618		0	0.90178
7.512503	563.4377		0	0.911736
7.661191	574.5894		0	0.920543
7.799563	584.9673		0	0.928348
7.928285	594.6214		0	0.93528
8.048004	603.6003		0	0.941446
8.15934	611.9505		0	0.946941
8.262885	619.7164		0	0.951848
8.359197	626.9397		0	0.956236
8.448798	633.6598		0	0.960167
8.53218	639.9135		0	0.963695
8.609799	645.7349		0	0.966865

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